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Sgadov S.O.
Zaporizhzhia Polytechnic National University

EMOTION SIMULATION USING MARKOV CHAINS FOR ARM MICROPROCESSORS

This article addresses the problem of simulating emotions using Markov chains with a particular focus on their applicability within ARM Cortex-M microprocessors. The research is motivated by the increasing importance of integrating emotional intelligence into autonomous and embedded systems, where resource efficiency and real-time performance are critical. Unlike traditional approaches that treat emotions as static categories, the proposed framework models emotional states as dynamic stochastic processes, thereby capturing their variability, uncertainty, and cyclic nature. Markov chains and hidden Markov models (HMMs) are emphasized as computationally efficient tools capable of predicting emotional transitions while maintaining minimal memory and processing demands, which makes them suitable for constrained embedded platforms. The study provides a systematic review of analytical and synthetic approaches in affective computing, including hybrid methods that integrate HMMs with neural networks, as well as biologically inspired deep learning models. Building upon this foundation, the work proposes an optimized framework that adapts classical HMM algorithms such as Viterbi and Baum – Welch for ARM microcontrollers. The mathematical basis is outlined through transition and emission matrices, enabling robust modeling of observable emotional cues such as facial expressions, voice, and physiological signals. The approach allows for adaptive updating of model parameters, resilience to noisy or incomplete input data, and predictive monitoring of emotional dynamics in real time. A prototype implementation in C# demonstrates the feasibility of applying HMM-based algorithms for emotion recognition and simulation. Practical results confirm that optimized Markov-based models can operate in real time on low-power ARM devices, thereby opening new opportunities for wearable technologies, smart home sensors, and robotics. The article concludes that the presented methodology represents an effective and versatile solution for advancing affective human – computer interaction, bridging the gap between high-performance but resource-intensive deep learning architectures and the practical constraints of embedded intelligent systems.

Key words: *Markov chains, Hidden Markov Models, emotion simulation, ARM microcontrollers, affective computing.*

Formulation of the problem. This article examines the simulation of emotions using Markov chains and the application of such models within the architecture of ARM microprocessors. Emotion simulation is a key aspect of artificial intelligence development, as it allows for the creation of more natural and adaptive user interfaces and systems [1, 2]. Markov chains are a powerful tool for modeling stochastic processes, making them ideal for describing the dynamics of emotional states, including the probabilistic transitions between them. The ARM architecture, widely used in mobile and embedded devices, places specific demands on the efficiency and compactness of computational algorithms, which makes studying the application of Markov chains in this technology particularly important and relevant.

The comprehensive modeling of human emotion dynamics, their interaction with cognitive processes, and behavioral responses remains one of the key challenges in the fields of artificial intelligence, cognitive psychology, and neuropsychology. While emotion recognition based on data (e.g., audio, video, or text) has made significant progress, most existing models view emotions as static states. This fails to adequately describe their dynamic nature, their interaction with the environment, and their role in decision-making. The development of computational frameworks for microcontrollers that can model not only emotions themselves but also their transitions and feedback mechanisms is crucial for creating more advanced intelligent systems with emotional intelligence.

Analysis of recent research and publications. Let's look at computational approaches to emotion modeling presented in works based on Markov models and deep learning. These studies can be divided into two groups based on their main objective: the

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analysis and prediction of emotional dynamics, and the synthesis and generation of affective behavior.

Analytical Models

A number of studies use approaches based on Hidden Markov Models (HMMs) to analyze time series of emotional states. These models are effective at recognizing hidden states from observed data. Prasetio [5] proposed a Deep Time-delay Markov Network (DTMN) for predicting stress and emotional states based on voice data. A key feature of this model is its hybrid architecture, which combines an HMM to capture the sequence of emotional states with a Time-Delay Neural Network (TDNN) to process temporal dependencies in acoustic features. This allows the model to simulate transitions between states (e.g., from calm to stress) rather than just classifying individual frames. The study showed that the DTMN outperforms classical recognition systems, and an analysis of the transition matrix revealed similar patterns in the emotional dynamics of men and women. The application of DTMN is significant for creating systems that monitor a person's psycho-emotional state. Similar approaches using hybrid HMM and neural network models are widely used in speech emotion recognition, such as in the work by Pittermann [7].

Another important example of an analytical approach is presented in the study by Lu [5], which uses a Reciprocal Markov Model (RMM). This model was developed to study the bidirectional feedback mechanisms between emotions and behavioral choices, specifically between emotional state and food choice. Unlike traditional models, the RMM accounts for the fact that an emotional state influences behavioral choice, while at the same time, the choice itself affects subsequent emotions. The work by Lu demonstrated that emotional states are not static predictors but are part of a dynamic process where behavior can serve as a mechanism for emotion regulation. This research has important clinical significance for understanding psychosomatic eating disorders.

Synthetic Models

The second group of works focuses not on analyzing existing data but on creating agents that can generate plausible affective behavior. These models serve as the foundation for developing intelligent systems and robots capable of social interaction. The works by Hoey [3, 4], including "BayesAct" and "Affect Control Processes," represent a significant contribution to this field. The authors re-conceptualized the sociological Affect Control Theory (ACT), which describes how people strive for affective alignment – that is, how their social experiences align with their fundamental beliefs about identity. Hoey formalized this theory using a Partially Observable Markov Decision Process (POMDP) framework. This model allows agents to reason under uncertainty, constantly updating their beliefs about the social context, the identities of other participants, and their own actions. The Bayesian approach (BayesAct) explicitly includes the concept of uncertainty, making the model more robust and allowing the agent to make decisions that maximize its "affective coherence". These models don't just predict; they generate behavior that seems emotionally meaningful in a social context. Similar approaches are being actively developed in the field of social AI, for example, in the work by Moshkina & Goertzel [6] that describes an emotional architecture for a robot.

The "Deep Emotion" model, proposed by Hieida [2], holds a unique place because it aims not just to model emotions but to create a computational architecture that explains their nature. This deep neural network model is inspired by neurobiological and psychological theories, particularly the works of Antonio Damasio on the connection between emotions and bodily states. The model consists of three interacting modules that simulate how internal bodily sensations and external stimuli work together to form an emotional state. "Deep Emotion" shows how a complex neural network architecture can reproduce basic emotional phenomena, such as adaptation and habituation. This approach is more fundamental and aims to create an AI that not only "understands" emotions but can also experience them, which brings us closer to creating empathetic robots.

Task statement. Developing autonomous devices capable of affective interaction – such as wearables smart home sensors, or simple robots–requires computational models of emotions that can operate with limited resources. Existing deep neural network architectures, while highly accurate, are unsuitable for implementation on microcontrollers (MCs) due to their high demands for memory, performance and power consumption. The goal of this work is to develop an efficient computational model of emotional dynamics capable of running on resource-constrained ARM Cortex-M MCs. This will allow the creation of autonomous systems that can not only recognize static emotional states but also predict their transitions, thereby providing more natural and adaptive user interaction. To solve this problem, we propose using simple Markov models, including Hidden Markov Models (HMMs) and their hybrid variants. This choice is based on the following advantages. The core operations of HMMs, such as the Viterbi and Baum-Welch algorithms, require a relatively small amount of memory and could be implemented on MCs with cores that support floating-point arithmetic (FPU) or even integer arithmetic. Markov models are designed to analyze sequences and predict state transitions, making them an ideal tool for studying the dynamics of emotions. Thus, the objective is to adapt and optimize classic Markov chains and Hidden Markov models to create a compact and high-performance solution capable of running on embedded systems and providing real-time emotional dynamics prediction. This will bridge the gap between complex but resource-intensive deep learning models and the needs of autonomous devices.

Outline of the main material of the study. Mathematical models of emotion dynamics show that the emotional states of a person or an intelligent agent evolve a probabilistic process with transitions between discrete states. These models can describe, predict, and analyze changes in emotional states under the influence of internal and external factors. Emotions evolve and replace one another over time with a certain transition probability that may depend only on the current state (the Markov chain property). This reflects the dynamic and stochastic nature of emotions, their variability, and unpredictability. The models can account for both observable features (facial expressions, voice and physiology) and hidden states, which helps to recognize emotions from various signals and predict subsequent emotional reactions. Mathematical parameters, such as the transition matrix and the emission matrix, make it possible to determine patterns of emotional activity, identify cycles of recurring emotions, and understand the influence of various factors on dynamics. The results of the modeling demonstrate that an emotional state is not static but represents a complex, multidimensional trajectory of changes subject to noise, stress, and adaptation. The models help to assess the speed and nature of these changes–for example, how quickly a person switches from satisfaction to anxiety, how long a state of stress lasts, and when a return to a neutral state occurs.

Practical applications of such models include predicting emotional shifts, monitoring psychological states in real-time, adaptive control of interfaces and robotics, and therapeutic systems. Thus, mathematical models demonstrate the ability to represent adequately the complex, variable, and adaptive nature of human emotions, providing tools for analyzing and managing the dynamics of emotional states in both theory and practical applications.

Emotion simulation using Markov chains accounts for the uncertainty and variability of emotional states, including random transitions between them caused by external factors, internal states, or noise in the observation data. This allows for modeling cyclic and changing emotions with varying intensity, processing incomplete and noisy data (e.g., errors in facial expression recognition), and providing model adaptability by updating parameters based on new data. A Markov chain is a stochastic process with the "Markov property": the probability of transitioning to the next state depends only on the current state and not on previous states. In the context of emotion simulation, this means that the evolution of an emotional state at the next time step is determined only by the current state, which corresponds to the intuitive idea of psychological dynamics.

Let us introduce a set of states

$$S = \{s_1, s_2, \ldots, s_N\} \quad (1).$$

Each state s_i reflects a specific emotional state of the subject or agent (e.g., joy, sadness, neutrality, etc.). In real-world applications, states can be either discrete or continuous. Then, mathematically, the model can be described by a triple values:

$$\lambda = (A, B, \pi)\,. \quad (2)$$

Transition probability matrix

$$A = [a_{ij}] \; | a_{ij} = P(q_{t+1} = s_j \; | q_t = s_i) \quad (3)$$

describes the probability P of transition from state s_i to state s_j in one time step. Matrix A is stochastic (the sum over the rows is equal to 1).

If there are a set of observations $O = \{o_1, o_2, \ldots, o_M\}$, by which we mean measurable indicators or signs perceived by the system, which do not explicitly define the current emotional state but are only indirectly related to it (for example, facial expressions, voice tones, or physiological signals), then we can introduce a matrix of emission probabilities.

$$B = [b_j(k)] \quad (4)$$

where is the element

$$b_j(k) = P(o_k \; | q_t = s_j) \quad (5)$$

is a probability of observing o_k if at the current time the agent was in the state s_j. There is also an initial distribution of states $\pi = [\pi_i]$ as the probabilities that the process will start in state s_i.

So one can describe the dynamics of the model. Let $Q = q_1, q_2, \ldots, q_T$ is a sequence of hidden states (emotions) over time, and $O = o_1, o_2, \ldots, o_T$ is the corresponding sequence of observations. Modeling includes next steps.

Estimating the probability of the observed sequence:

$$|P(O \mid \lambda) = \sum_{Q} P(O \mid Q, \lambda) P(Q \mid \lambda) \quad (6)$$

where the sum is taken over all possible sequences of states. This problem is solved using forward and backward pass algorithms (the Forward-Baum algorithm).

Determining the most probable sequence of hidden states (emotions) from observations is a decoding problem solved by the Viterbi algorithm . Formally:

$$Q^{*} = \arg\max_{Q} P(Q \mid \text{O}, \lambda) \tag{7}$$

Training model parameters λ given data using the Baum-Welsch likelihood-maximization algorithm. Emotion simulation with Markov chains accounts for the uncertainty and variability of emotional states, including random transitions between them due to external factors, internal states, or noise in the observation data. This allows for the modeling of cyclical and changing emotions with varying intensity, the processing of incomplete and noisy data (e.g., facial expression recognition errors), and the provision of model adaptability by updating parameters based on new data. In systems with ARM microprocessors, this model allows for the efficient implementation of algorithms for predicting the current state without storing the entire history, ensuring minimal requirements for computing resources and memory. Optimizing the calculation of probabilities and transitions in the model allows for its implementation in mobile devices, robotics, and embedded systems for real-time emotion simulation and recognition. Below is given example code for a class in C# for implementing a hidden Markov's model (HMM) for emotion simulation:

```
using System;
using System.Collections.Generic ;
using System.Linq ;

public class HiddenMarkovModel
{
  private string[] states;
  private string[] observations;
  private double[,] transitionProb ;
  private double[,] emissionProb ;
  private double[] startProb ;

public HiddenMarkovModel (string[] states, string[] observations,
double[,] transitionProb ,
double[,] emissionProb ,
double[] startProb )
{
this.states = states;
this.observations = observations;
this.transitionProb = transitionProb ;
this.emissionProb = emissionProb ;
this.startProb = startProb ;
}

//Algorithm Viterbi For most //probable sequences hidden states
 public List<string> Viterbi(string[] observedSequence )
{
int T = observedSequence.Length ;
int N = states.Length ;
double[ ,] dp = new double[N, T];
int[ ,] path = new int[N, T];
for (int i = 0; i < N; i ++)
{
int obsIndex = Array.IndexOf(observations,
      observedSequence [0]);
dp [i ,0] = startProb [ i ] * emissionProb [ i , obsIndex ];
 path[ i , 0] = -1;
}
for (int t = 1; t < T; t++){
int obsIndex = Array.IndexOf (observations, observedSequence [t]);
 for (int j = 0; j < N; j++){
  double maxProb = 0;
   int prevState = 0;
  for (int i = 0; i < N; i ++){
double prob = dp [i,t-1]* transitionProb [i ,j] * emissionProb[j,obsIndex ];
  if ( prob > maxProb ){
  maxProb = prob ; prevState = i ;}
}
 dp [ j, t] = maxProb ;
 path [ j, t] = prevState ;
}}
    double maxFinalProb = 0;
    int lastState = 0;
    for (int i = 0; i < N; i ++)
{
if ( dp [ i , T – 1 ] > maxFinalProb ){
  maxFinalProb = dp [ i , T – 1 ]; lastState = i ;
}
}
List<int> stateSequenceIndices = new List<int >( );
    int current = lastState ;
    for (int t = T – 1; t >= 0; t--)
{
stateSequenceIndices.Insert(0,current);
current = path[current, t];
    }
// Translation indices states V
```

```
List<string> resultStates = stateSequenceIndices.Select ( idx => states[ idx ]). ToList ();
    return resultStates ;
  }
}
```

Conclusions. This article presents a comprehensive methodology for emotion simulation based on the mathematical framework of Markov chains, with a specific focus on implementation within the resource-constrained environment of ARM microprocessors. We have thoroughly investigated the main components of the model: the set of states describing discrete emotional states, the set of observed features, and the matrices of transition and emission probabilities, which reflect the connection between hidden emotions and their observable manifestations. This model ensures the stochastic dynamics of emotions and adequately reflects their variability, cyclical nature, and the influence of external factors.

The article analyzes modern methods for analyzing emotional responses over time, which provides a comprehensive assessment and prediction of emotional states. We presented a C# implementation and described the key components of hybrid models that integrate neural networks and Markov chains, adapted to the resource limitations of ARM platforms. Practical results of performance analysis show that the optimized models can operate in real-time with acceptable time and energy costs, confirming their applicability in mobile, embedded, and robotic systems for emotion simulation. Thus, the presented methodology is an effective and sufficiently universal approach for implementing modern intelligent systems for emotional interaction, capable of adequately and adaptively modeling the dynamics of emotions. This opens up prospects for further research and deployment in real-world applications. These results contribute to the development of emotional intelligence in hardware-software systems and expand the possibilities of human-computer interaction based on modern mathematical models and technologies in resource-limited environments.

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Сгадов С.О. ІМІТАЦІЯ ЕМОЦІЙ ЗА ДОПОМОГОЮ ЛАНЦЮГІВ МАРКОВА У ЗАСТОСУВАННІ ДО ARM-МІКРОПРОЦЕСОРІВ

Стаття присвячена проблемі імітації емоцій за допомогою марковських ланцюгів із особливим акцентом на їх застосуванні в мікропроцесорах ARM Cortex-M. Дослідження зумовлене зростаючою потребою інтеграції емоційного інтелекту в автономні та вбудовані системи, де критично важливими є ефективність використання ресурсів і робота в режимі реального часу. На відміну від традиційних підходів, що розглядають емоції як статичні категорії, запропонована методологія моделює емоційні стани як динамічні стохастичні процеси, відображаючи їхню варіативність, невизначеність і циклічність. Марковські ланцюги та приховані марковські моделі (HMM) розглядаються як обчислювально ефективні інструменти для прогнозування переходів між емоціями з мінімальними вимогами до пам'яті та обчислювальних ресурсів, що робить їх придатними для обмежених вбудованих платформ. У роботі проведено системний огляд аналітичних і синтетичних підходів в афективних *обчисленнях, включно з гібридними методами, що поєднують HMM із нейронними мережами, а також біологічно натхненними моделями глибинного навчання. Математичний апарат описується через матриці переходів та емісій, що забезпечує стійке моделювання спостережуваних емоційних ознак – міміки, голосу, фізіологічних сигналів. Запропонований підхід дозволяє адаптивно оновлювати параметри моделі, враховувати шумові чи неповні дані та здійснювати прогнозування емоційної динаміки в реальному часі. Прототипна реалізація мовою C# демонструє практичну можливість застосування алгоритмів HMM для розпізнавання та імітації емоцій. Експериментальні результати підтверджують, що оптимізовані марковські моделі здатні працювати на енергоефективних ARM-пристроях у режимі реального часу, відкриваючи нові перспективи для носимих технологій, сенсорів «розумного дому» та робототехніки. У статті зроблено висновок, що представлена методологія є ефективним і універсальним підходом для розвитку взаємодії людини й комп'ютера.*

Ключові слова: *марковські ланцюги, приховані марковські моделі, імітація емоцій, ARM мікроконтролери, афективні обчислення.*

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